

Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 1 (2010) 2793–2800

**Procedia
Computer
Science**

www.elsevier.com/locate/procedia1st Workshop on Recommender Systems for Technology Enhanced Learning (RecSysTEL 2010)

Modeling recommendations for the educational domain

Olga C. Santos*, Jesus G. Boticario

aDeNu Research Group, UNED. Calle Juan del Rosal, 16. Madrid 28040. Spain.

Abstract

Recommendations for technology enhanced learning scenarios have differences from those in other domains as recommendations in e-learning should be guided by educational objectives, and not only by the users' preferences. Most efforts so far have focused mainly on researching algorithms that retrieve relevant learning materials to the learner, but other kind of recommendations can be provided due to the richness in services and functionality available in educational web-based scenarios. To find out relevant recommendation items from an educational point of view, a top down perspective can be used to design recommendations, especially for formal learning scenarios. To cope with these needs, we have defined a semantic recommendations model that can be used to describe the recommendations for technology enhanced learning.

© 2010 Published by Elsevier B.V. Open access under [CC BY-NC-ND license](http://creativecommons.org/licenses/by-nc-nd/4.0/).

Keywords: Recommendation model; formal learning; educational recommender systems; technology enhanced learning.

1. Introduction

Recommender systems were developed to support web users dealing with large information spaces by pre-selecting information a user might be interested in, especially when users have insufficient experience in the alternatives [4]. The educational domain entails strong differences from other domains where recommendations have successfully been applied and provides additional recommendation opportunities as it is a rich-contextual domain where not only different types of objects can be recommended, but also different types of actions can be recommended to these objects to achieve an educational goal (e.g. post a message in the forum for self-reflection on the contents read).

Two approaches can be considered when developing recommender systems for education: i) a top-down approach suitable for formal learning, where the structure, learning materials and learning plans are maintained by domain professionals, and ii) a bottom-up approach suitable for informal learning as learning takes place in a self directed way within learning networks where learners interact with information sources shared in the network [2]. Our work is focused on the first approach.

* Corresponding author. Tel.: +34 91 398 93 88; fax: +34 91 3988895.

E-mail address: ocsantos@dia.uned.es.

2. Background

Although educational recommender systems (ERS) share the same key objectives as e-commerce applications recommenders (i.e. helping users to select the most appropriate item from a large information pool), there are some particularities that make not possible to directly apply existing solutions to ERS. In fact, recommender systems are strongly domain dependant [2], so the particularities of each domain should be taken into account. As previously discussed in [8], recommendations in educational scenarios should be pedagogically guided by educators, and not only by learners' preferences.

Several ERS have been proposed in the literature [3]. The most common approaches for formal learning focus on recommending suitable materials or learning activities but do not consider the recommendation opportunities derived from the contextual richness of the educational domain. Recommendation in the e-learning context could be diverse, e.g. as simple as suggesting a web resource, or more interactive (i.e. an on-line activity) such as doing an exercise, reading a posted message on a forum or running an on-line simulation [9]. Due to the particularities of the educational domain, the involvement of the educator is required to find out relevant recommendations from an educational perspective. Thus, there is a need to support educators with resources that help them in describing the recommendations required for their courses searching for a compromise between exploring new recommendation opportunities and increasing the educators' workload to manage the course.

Currently there are research works focused on recommending learning materials following known strategies, which were previously applied to other domains, but the usage of ERS introduces new challenges from the design and run-time viewpoints: 1) understanding the needs of learners when receiving recommendations in technology enhanced learning scenarios, and 2) offering educators a control mechanism on what is recommended to their learners. Next, we present our approach to cover these challenges.

3. The TORMES Recommendations Model

We have been working in the development of a semantic ERS, called TORMES which stands for Tutor-Oriented Recommendations Management for Educational Systems. TORMES currently follows a rule-based approach to select the appropriate recommendations (i.e. it consists in a knowledge-based recommender according to [1]). The reason to use a knowledge based recommender is the fact that currently the recommendation opportunities within e-learning platforms have not been extensively explored, and therefore, there is a need for systems that allow educators understanding the recommendation needs and controlling the recommendations offered to their learners. Educators need resources that allow them to experiment designing recommendations to be delivered to their learners. Experiences with educators have shown that they are interested in them [5].

To support this, we are applying user-centered design methods to help educators eliciting relevant recommendations that help them in supporting their learners through the e-learning platforms [7] and which can be delivered to their learners though a ERS [6]. Since the elicitation process is time consuming, a medium-term goal is to automate this design process with appropriate algorithms. We expect that once experiences are carried out with this top-level approach, bottom-up approaches that do not require the direct human involvement (such as collaborative filtering) can be applied to reproduce those recommendations elicited by educators. Both approaches are to be combined and supported by TORMES in the future.

Thus, our approach differs from traditional approaches of ERS and demands effort from the educator. We consider that there is a wide variety of recommendation opportunities in e-learning platforms which have not yet been extensively experienced to understand how they can contribute to specific educational goals. Therefore, we use TORMES to involve the educator in identifying relevant recommendations from an educational perspective. In this way, a wider scope of issues beyond recommending learning contents to learners (which is typically provided by ERS) may be identified. With this approach, we are going back to the original definition of a recommender system as systems in which "people provide recommendations as inputs which the system then aggregates and directs to appropriate recipients" [4].

This approach requires that the educator is supported to make explicit what (i.e. an action on an object of the e-learning platform) should be recommended to a particular learner to achieve a certain educational goal. The educator can even think on high level values for some conditions that should occur for the recommendation to be delivered to the learner. These conditions are be used in the rule that describes the recommendation delivery. For instance, to

promote self-reflection on some contents just read (i.e. the educational goal) the educator may propose a recommendation for those learners that are not very participative in the communication tools. However, it is probably quite difficult for the educator to identify when a learner is not very participative in the communication tools. Thus, to identify this value, data mining techniques (e.g. clustering or classification) can be applied to mine the appropriate values to use from past interactions of learners with the e-learning services.

To support the description of the recommendations by the educator in a way that can be later processed by the algorithms, we have proposed a semantic model to describe the recommendations. The model covers the following objectives:

- supporting the teacher in describing recommendations for technology enhanced learning scenarios
- presenting information to the user about the recommendations offered
- providing semantic information to facilitate the reasoning by the algorithms

The recommendations model facilitates the management of recommendations at design time to support the runtime operation. An initial version of the model was presented in [5]. Its application in several scenarios has motivated a revised version, which is presented here.

The model allows describing i) what should be recommended, ii) how the recommendation should be communicated, iii) when the recommendation should be offered, iv) why the recommendation is delivered and v) which are the recommendation characteristics. Recommendations are defined as links, which is a typical output of recommender systems. They consist in a sentence which advises the user to carry out an action on an object in the platform together with some metadata about the recommendation features. The information presented to the user includes an introductory text plus a list of suggested actions to do by the user on objects on the e-learning platform. Each of these suggestions is a recommendation. Examples of recommendations are i) replay a message already posted in the forum, ii) read a message posted in the forum by a classmate, iii) upload a file to share your work, iv) chat with a classmate, etc. In principle, any action on any platform object could be recommended. However, the final decision depends on the educational criteria, which determines its utility taking into account the recommendations design methodology.

The model defines different sets of elements, as introduced below. Table 1 presents an example of a recommendation described in terms of these elements.

3.1. Elements of the model

Five main elements are defined in the model: 1) the type, 2) the content, 3) the runtime information, 4) the justification and 5) the semantic information. In turn, each of them is divided into other sub-elements, as follows.

The **type** element provides information about *what* is recommended, and consists in:

- The **object**: any generic item of a service in the learning platform (e.g. a file of the file storage, a message of a forum, a calendar event...).
- The **action**: what the learner is told to do with the object. Two different types of actions are identified: i) passive actions (e.g. reading, visiting) or ii) active actions (e.g. selecting, posting, commenting, filling in, changing ...). The seconds are potentially more relevant, and imply a visit to a particular page of the platform and the specific action on the object that is shown in that page.

The **content** element provides information about how to communicate the recommendation, and consists in:

- The **text**: describes to the learner the action recommended and is to be shown to her in the e-learning platform graphical user interface.
- The **link**: part of the text which contains an HTML link that points to the object recommended
- The **title**: go with the link and describes the page where the learner will go if she clicks in the link of the recommendation

The **runtime information** provides the values for the rules and defines when the recommendation has to be delivered to the learner, and consists in.

- **Restrictions**: inform about the validity of the recommendation, to facilitate ruling out the checking of recommendations that are out of date or not applicable.

- **Applicability conditions:** define what values should take place for a user and her context at runtime to be given the corresponding recommendation. In order to facilitate the interoperability with other systems, it is desirable that the conditions are specified in terms of available standards (e.g. IMS family of educational specifications).
 - Regarding the *user information*, the following values can be considered: the role, the learning styles, the technology level, the collaboration level, the accessibility preferences, some interaction data, the knowledge level on the learning objectives, the interest in the course concepts, etc.
 - In turn, for the *context information*, the values can take into account a) platform information (e.g. recommendations may be given to the learner when she is working on a specific course environment with a given set of resources and doing certain actions on specific objects; b) the device capabilities, as some recommendations may not be suitable depending on the capabilities of the device being used; and c) instructional design issues, which provides the situation of the learner is in the course context, especially, the learning objective (or competence) being addressed in the current activity. When designing a recommendation, not all the above properties should be filled in, only those that should be checked at runtime for each specific recommendation.

The **justification** element provides information about why a recommendation has been produced, and consists in:

- The **rationale**: refers to the educational foundations of the recommendation, that is, the educational goal that is expected to be achieved by offering the recommendation to a specific learner
- The **explanation**: provides a reason for the user to whom the recommendation has been delivered (i.e. the learner), in order to motivate her and support trust in the system.

The **semantic information** provides information about which are the recommendation's features. Initially is to be provided by the educator when eliciting the recommendations with the user-centered design methods. It consists in:

- The **category**: the criteria in which the recommendation is focused. An initial set of categories has been proposed: motivation, learning styles, technical support, previous knowledge, collaboration, interest, accessibility and scrutability, but it can be refined with the user-centered design methods proposed in the methodology.
- The **course stage**: differentiates the course situation, e.g. if the learner is getting used to the platform and or the course operation or not. Currently, the following values are defined: i) getting used to the platform, ii) getting used to how the course is organized, iii) reading contents, iv) doing activities, v) taking evaluation, and vi) applicable to any stage.
- The **origin**: shows the source that originated it, which can be one of the following: i) course design (the recommendation was predefined during the design of the course); ii) preferred (the recommendation is based on the user preferences); iii) popular (the recommendation took into account the user interactions with similar profile), or iv) tutor (the tutor in charge of the support in the platform has defined this recommendation based on his/her experience).
- The **relevance**: prioritize the recommendations to be offered in the case that there are several recommendations that match the current user and context.

The elements of the model are defined domain independent. Nevertheless, when the specific values are given, they are matched to the particularized of the educational domain.

Table 1 provides an example of how the above elements can be used to describe a recommendation.

Table 1. Example of a recommendation

Recommendation 1: Read the tutorial on how to use the platform			
Object: tutorial	Action: read		
Content (text + link): “Visit the <u>platform tutorial</u> so you get familiarized with it”			
Title: “Access to the page with the platform tutorial”			
Applicability conditions: <ul style="list-style-type: none">• The learner is new to the platform• The learner has interacted with the platform several times• The learner has not accessed the tutorial• The learner has not contributed in any of the platform services			
Restrictions <ul style="list-style-type: none">• There is a tutorial in the platform			
Category: technical support	Course stage: Getting used to the platform	Origin: tutor	Relevance: 4.2
Rationale: make the learner get familiarized with the platform			
Explanation: “Since you are new to the platform and you have not yet used the services available in the platform, you can access this tutorial to get familiarized with the platform operation”.			

4. Perception of the model

We have carried out some formative evaluations to assess our approach. In this paper we report the results of an experience with 40 users in an online course that was carried out to analyze the perception by the users of the recommendations model proposed. Relevant data from the sample regarding their background is the following: accessibility experts (50%), people with disabilities (20%), experience with web-based applications for learning (100%), experience with web-based applications for teaching (70%).

4.1. The settings

We selected an accessible SCORM-based course on how to use the dotLRN [13] learning management system (LMS) called ‘Discovering the platform’ produced following the ALPE methodology [10]. A course space was created in dotLRN to deliver it. Within this course space, several services were configured: a forum, the file storage area, the calendar, some frequently asked questions, a chat room, a personal blog, some questionnaires and access to the individual statistics of the interaction in the course. Moreover, a help section summarizing the platform functionality was also provided. Users had also access to fill in Felder’s learning style questionnaire [11]. The course was designed following the approach of learning by doing [12], which means that small activities were required involving the usage of the different services of the platform. Although formally it was described as a 5-hours course, the activities could be performed in no more than one hour. The recommendations infrastructure was added to dotLRN [6] to offer some personalized recommendations at certain moments of the course. Once followed each recommendation by the learner, it was no longer displayed to her. Three runs of the course were carried out, the three of them framed in several editions of a couple of summer courses. A blended approach was followed in this case.

During the summer courses, learners were given access to the course for an hour. Afterwards, they could access the course on line whenever they wanted. The reason for this face-to-face session of one hour length was to observe the users as they interacted with the environment. No other interaction was done with them, so they were not supported with online tutoring, but had the recommendations support. The length of one hour was chosen because it was computed as a reasonable time to carry out the course activities.

The first summer course entitled “Accessibility and disability in the University: a development based on ICT” was organized by UNED in July 2008 and July 2009. The participants in this course were mainly accessibility experts and people with disabilities. The second course entitled “Services of the Web: applications towards the frontiers of knowledge” was organized by the UIMP in August 2008. The participants in this course had experience in using web-based applications for learning and teaching. Thus, we compiled a heterogeneous sample of users to assess the system with recommendations.

Taking the proposed model as our design framework, we defined thirteen recommendations to be given to the users in different course situations. When the users entered the system, they were recommended to read the help section on the platform usage (Rec_1) and to fill in the learning style questionnaire (Rec_2) to be able to adapt the contents to their learning style. Moreover, they were also recommended to go to the course contents (Rec_3). To promote collaboration, once in the course space they were suggested to present themselves in the course forum (Rec_4). When learners had followed the course contents, they were suggested to fill in a questionnaire about their experience in the course (Rec_13).

We also defined one recommendation for each of the extreme values of the four dimensions of the Felder’s questionnaire. These recommendations were only given when the users had a strong preference for one of the extremes of the learning style dimension. In this way, depending on the outcomes of the Felder test, the learners received different recommendations, as follows Active learners were recommended to chat (Rec_5), reflective learners to comment a blog (Rec_6), sensing learners to reading the General FAQ (Rec_7), intuitive learners to consult the Calendar FAQ (Rec_8), visual learners to read a graphical description and upload a new version (Rec_9), verbal learners to read a textual description and upload a new version for a (Rec_10), sequential learners to access the introduction item of the course (Rec_11) and global learners to read a forum message where an overview of the course was given (Rec_12). It has to be considered that the objective here was not to validate if these eight recommendations properly applied the Felder theory, but to present different plausible actions personalized to the users’ features so they could experience a typical behavior of the recommender system and feed back on it. To define appropriate recommendations the user-centered methodology proposed has to be followed.

4.2. The results

To cope with ethical considerations and privacy concerns, the analysis of the experiences was done by using the internal user identifier created by the system. For the analysis of the perception of the recommendations model, we took into account the responses given to the questionnaire at the end of the one-hour face to face session. From the 40 users who took part in the experiences, 25 valid responses were obtained in the questionnaire (62.50%). Partial results of this experience (analyzing the 2008 runs of the course) were published elsewhere [5].

Figure 1 shows the global perception of the recommender. Although there were four possible options, none of the learners selected that the recommender was a nuisance or that they had not noticed it. If we compare this result with the previous analysis (in particular the first run of the course) it can be noticed that the number of users who thought that the recommender is yet another service, has increased. As their satisfaction was rated high, the conclusion from these results can be that users are already demanding this personalized support in LMS and do not surprise them when the LMS offers it.

Figure 2 focuses on the metadata used to describe the recommendation. When the experience was carried out, the course stage metadata was not considered yet in the model, and therefore, was not assessed by the participants. When filling the questionnaire, participants were allowed to select as many as elements they considered relevant for them. The percentage shown in Figure 3 is computed considering the ratio of participants who selected each element among the total number. It can be seen that the category and the explanation are the two most relevant elements, as more than half of the participants have selected it. As expected, the algorithm (i.e. technique) used are not so relevant. For this reason, it has been omitted in the revised version of the model that is presented in this paper.

In Figure 3 we analyze which values of the origin element the participants appreciated more. In this question, participants were also able to select as many options as they wished. In the same way as before, the percentage shown is computed considering the ratio of participants who selected each element among the total number of responses. Moreover, they were also asked for new origins, but nobody suggested a new one. The results shown that participants trusted more the recommendations coming from the tutor, and then, they appreciated those that took into account their own preferences.

In Figure 4 we analyze which are the categories –from the ones initially proposed- that users appreciated more. As before, participants could select as many options as they wished. Moreover, they were also asked to suggest new categories, but nobody provided a new one. The analysis of the results shows that according to these participants, the most relevant categories are learning styles, previous knowledge and interest.

Finally, participants were asked if they would use the recommender system for their teaching. All participants who had experience with web-based applications for teaching answered positively to this question.

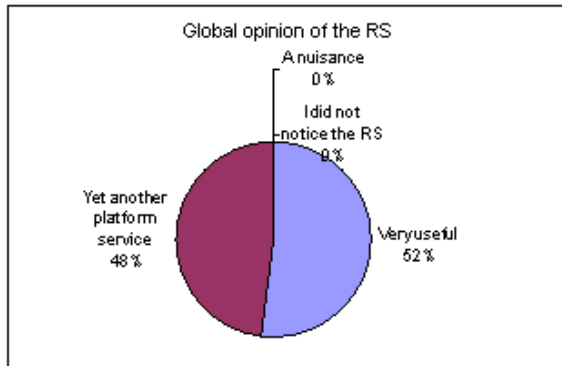


Figure 1. Global opinion of the recommender

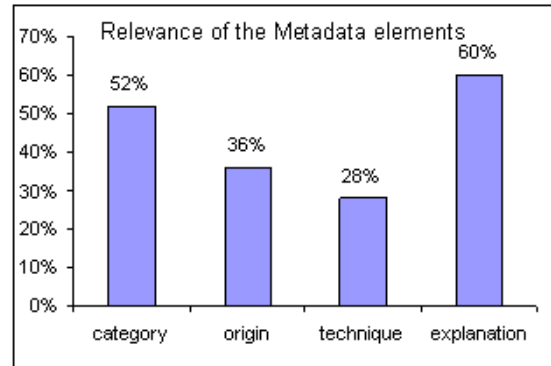


Figure 2. Relevance of the metadata elements

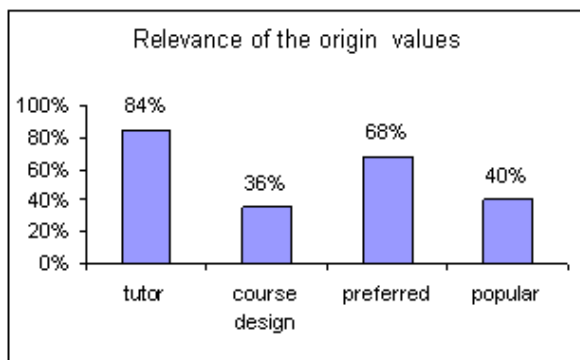


Figure 3 Relevance of the origin values

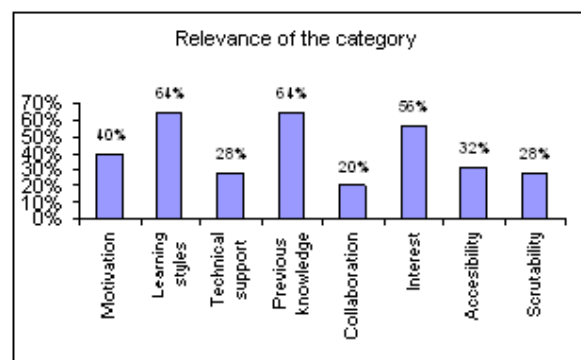


Figure 4 Relevance of the category values

These formative evaluation experiences served us to get the feeling of users towards this semantic approach to describe recommendations. From the results, it seems that users are interested in being informed about the recommendation features. On-going works are to apply the methodology proposed to elicit recommendations combining user-centered methods with educators and data mining techniques on interaction data and carry out summative evaluations of the whole system when these recommendations elicited are delivered to the learners in the course. We aim to evaluate not only the performance of the recommender system as a whole, but also the individual impact of each recommendation in the user to discover relevant recommendations for technology enhanced learning scenarios.

5. Discussion

The current situation in ERS is the reduced number of experiences on recommending to learners the usage of an object of the e-learning platform for an educational goal, despite the richness of recommendation possibilities in the educational domain. In this paper we have presented the recommendations model used by TORMES semantic recommender system, which is prepared to support formal learning scenarios. In a formal learning approach, when students are interacting with an e-learning platform, they should be supported in their learning in a personalized way. Since current e-learning platforms rarely provide adaptation capabilities, TORMES has been designed

following a service oriented architecture so it can be integrated with this platforms through web services. The goal is twofold: i) to provide the educator with the tools to design educational-based recommendations on the required objects available in the e-learning platform, and ii) offer this recommendations to the learners taking into account their description in terms of the model. Details on the implementation of TORMES and its integration with a well-known learning management system –i.e. dotLRN– are provided elsewhere [6].

This recommendations model is complemented with a methodology to design recommendations that combine user-centered design methods and data mining techniques. The idea behind that methodology is to facilitate the involvement of the teacher in the process of designing recommendations for formal learning scenarios in web-based settings [7]. An analysis of the particularities of the educational domain and a review of the literature of recommenders systems for educational domains support the rationale of our approach. Some formative evaluations have been carried out to analyze to get qualitative feedback that helps us to understand the users' perception on the recommender and its impact on them. The results obtained suggested continue working in this direction.

Acknowledgements

Authors would like to thank the European Commission and the Spanish Government for funding the projects of aDeNu group that have supported this research work. In particular, EU4ALL and ALPE (the former) and ATODOS and A2UN@ (the later). Moreover, authors would also like to thank the members on aDeNu involved in the developments required as well as the users who participated in the experiences.

References

1. Burke, R. (2002). Hybrid recommender systems: survey and experiments. *User Modeling and User-Adapted Interaction* 12, 331-370.
2. Drachsler, H. (2009). Navigation support for learners in Informal Learning Networks. Open Universiteit Nederland.
3. Manouselis, N., Drachsler, H., Vuorikari, R., Hummel, H. and Koper, R. (2010) Recommender Systems in Technology Enhanced Learning, in Kantor P., Ricci F., Rokach L., Shapira, B. (Eds.), *Recommender Systems Handbook: A Complete Guide for Research Scientists & Practitioners*.
4. Resnick, P and Varian, H.R. (1997) Recommender systems. *Communications of the ACM* Vol. 40 (1997), pp. 56-58.
5. Santos, O.C. and Boticario, J.G. (2008). Users' experience with a recommender system in an open source standard-based learning management system. 4th Symposium of the WG HCI&UE of the Austrian Computer Society on Usability & HCI for Education and Work.
6. Santos, O.C., Granado, J., Raffenne, E., Boticario, J.G. (2008) Offering Recommendations in OpenACS/dotLRN. *Int. Conf. on Community based environments*, Valencia
7. Santos, O.C. and Boticario, J.G. (2010). Usability methods to elicit recommendations for Semantic Educational Recommender Systems. *IEEE Learning Technology Newsletter* Volume 12, Issue 2 (April, 2010).
8. Tang, T., McCalla, G. (2003) Smart Recommendation for an Evolving E-Learning System. *Workshop on Technologies for Electronic Documents for Supporting Learning*, Int. Conference on Artificial Intelligence in Education.
9. Zaiane, O. (2002) Building a recommender agent for e-learning systems. *Proceedings of the International Conference on Computers in Education*, Auckland, New Zealand, December 2002, pp. 55-59.
10. Santos, O.C., Boticario, J.G., Fernández del Viso, A., Pérez de la Cámara, S., Rebate Sánchez, C., Gutiérrez y Restrepo, E. (2007) Basic skills training to disabled and adult learners through an accessible e-Learning platform. *12th International Conference on Human-Computer Interaction*.
11. Felder R. M., Silverman L. K. 2002. Learning and Teaching Styles In *Engineering Education*, *Engr. Education*, 78(7), 674–681 (1988) – Preface: Felder R. M., June.
12. Schank, R. C. y Cleary, C. (1995) *Engines for Education*. Lawrence Erlbaum, 1995.
13. Santos, O.C., Boticario, J.G., Raffenne, E., Pastor, R. (2007a) Why using dotLRN? UNED use cases. *FLOSS International Conference*.